Emotion Classification in Parkinson's Disease EEG using RQA and ELM

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Abstract*— Most of the earlier works focused on diagnosing the Parkinson's Disease (PD) through behavioral measures. Very few researches attempted to identify the emotion impairment in PD through EEG signals. The main objective of this work is to classify the emotions perceived by the PD subjects through audio-visual stimuli using Electroencephalogram (EEG) signals. EEG database of 20 subjects on PD and 20 NC is developed using a 14 channel wireless EEG device at a sampling frequency of 128 *Hz*. Audio-visual stimuli of six emotions (happiness, sadness, anger, fear, surprise, and disgust) are used to induce the emotions. The acquired EEG signals are pre-processed using the IIR Butterworth filter to remove the noises, artifacts, and interferences in EEG signals and used to derive three frequency bands (alpha, beta and gamma) of EEG data. Recurrence Quantification Analysis (RQA) is used to extract the two most significant features (Maximum Line Length, Maximum Vertical Line Length) from Recurrence Plot (RP). Besides, these features are combined together called ALL features. Therefore, three types of features were tested using one-way analysis of variance (ANOVA) to test its significance in classifying emotions in PD and NC and a five-fold cross-validation method is used to split the features into training and testing set. Finally, the Extreme Learning Machine (ELM) classifier with two different types of kernel functions used to classify the emotions of PD and NC. The maximum mean accuracy of 89.17%, 84.50% is achieved on NC and PD, respectively. The maximum individual class accuracy of NC/PD is sadness – 90.90/87.50, happiness – 91.10/84.30, fear – 88/84.10, disgust – 88.5/82.70, surprise – 87.4/84.60, and anger – 89.10/83.80. Experimental results indicate that RQA features are highly useful in detecting the emotions in PD compared to other methods and ELM gives the highest mean accuracy compared to other works in the literature.

Keywords—Emotion classification, Extreme Learning Machine, Recurrence Quantification Analysis, Parkinson's Disease, Electroencephalogram (EEG)

I. Introduction

One of the most common geriatric disorders in developing and developed countries is Parkinson's disease (PD). PD is mainly due to the loss of dopamine in the substantia nigra pars of the basal ganglia region in the brain. Thereby, the PD subjects are mostly subjected to the issues in speech, prosody, gestures, and muscular movements [1]. Most of the earlier works focused on diagnosing the PD through behavioral measures [2-3]. Recently, researchers have used EEG signals to diagnose the PD using Convolutional Neural Network (CNN) and developed Parkinson's diagnosis index to differentiate normal control and PD [4-5]. Besides the behavioral issues, PD subjects also subjected to cognitive and emotional impairment [6].

To date, these impairments are mostly investigated by the clinical neurologist using clinical assessment tools and these tools do not provide discerning information about the tangible level of impairment in PD. Because these tools mostly utilize the verbal responses of PD subjects and it may not be accurate in determining the emotional impairment level in PD. Several researchers started working on developing intelligent tools to effectively assess the level of emotional impairment in PD through different methods such as facial expressions, physiological signals, gestures, speech, and multi-modal approaches. Among the above-mentioned methods, physiological signals are more reliable and resourceful in identifying the emotional impairment level in PD. Since these methods are directly related to of central autonomic nervous system (CNS) and the Autonomic Nervous System (ANS) activity of the subjects and do not depend on the subject's verbal response to assess their emotional perception problem. Among the different types of biosignals, EEG is one of the most reliable and cost-effective methods of collecting useful information from brain electrical activity. The first work on emotional impairment detection in PD using EEG signals is reported in [7]. Very few researches attempted to identify the emotion impairment in PD through EEG signals [8-10].

In general, EEG signals are highly non-stationary and non-linear signals. Hence, non-linear features such as Hurst exponent, Bispectrum features, Detrended Fluctuation Analysis (DFA), Correlation dimension (CD), etc gives more meaningful information of EEG signal analysis [8-10]. In our earlier work, we used to detect the emotional impairment problem using EEG signals and achieved a maximum mean emotion classification rate of 87.34% on NC and 83.70% on PD on classifying six emotions [8]. Among the different types of non-linear feature extraction methods, Recurrence Plot (RP) is most widely used to study the complex behavior of the system through visual analysis. To the best of the author's knowledge, there is no work in the literature utilized RQA in emotion classification in PD using EEG signals.

The main objective of the present work is to classify the emotions of the PD using RQA features and to compare with NC to identify any emotional impairment in PD using EEG signals. This is the first work which utilizes RQA and ELM classifier to classify the emotions in PD. This paper is organized as follows: (a) introduction to PD and the need of emotion classification in PD using EEG signals is presented in section I (b) section II briefly discussed the methodology of the present work in emotion classification (c) section III analyzes the experimental results of emotion classification in PD and NC and (d) the conclusion of the present work is given in section IV.

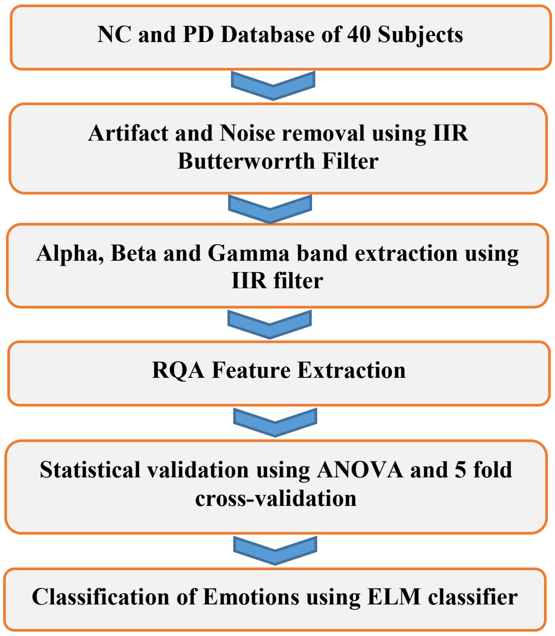

Fig. 1. Research methodology of facial emotion recognition using virtual markers.

II. Methods and Materials

This section presents the research methodology of the proposed emotion classification in PD using EEG signals. Fig 1 shows the methodology of the present work.

A. Database

In this work, the Emotiv 14 channel wireless EEG device is used to collect the EEG signals at a sampling rate of 128 *Hz*. 20 Parkinson's disease subjects up to stage IV and 20 Normal control who are age, education and gender-matched subjects are selected for the experiment and subjects have given written consent before participating in the experiment in Hospital University Kebangsan Malaysia (HUKM), Kuala Lumpur, Malaysia. Each subject is requested to watch 6 trials of video (audio-visual stimuli) for each emotion. The complete experimental protocol has been approved by the Ethical Committee in HUKM, Malaysia. All the subjects are requested to watch the six emotional video clips (happiness, sadness, surprise, fear, disgust, and anger) presented on the LCD screen. International Affective Picture System (IAPS) and International Affective Digital Sounds (IADS) databases used to prepare the emotional stimuli and the complete details of the database, inclusion and exclusion criteria of PD subjects, data collection environment, and setting can be found in [10].

B. Preprocessing of EEG signals

In this work, the IIR Butterworth 6th order filter is used to remove the high and low-frequency noises present in EEG signals. Hence, a cut-off frequency of 0.5 *Hz* to 49 *Hz* is used in the IIR filter to filter out the noises. Besides, the EEG signal amplitude of ±85μV is considered as an artifact and it is removed from the entire EEG signals traces before filtering to avoid any effect due to eye blinking, eye movement, and muscular movements.

C. Frequency band extraction

EEG signals are mostly analyzed over five different frequency bands such as delta (1 – 4 *Hz*), theta (4 – 8 *Hz*), alpha (8 – 13 *Hz*), beta (13 – 30 *Hz*) and gamma (30 – 49 *Hz*). In the case of emotion recognition, alpha (α), beta (β) and gamma (γ) bands give more insightful information about the emotional state changes in wakeful conditions and delta (δ) and theta (θ) bands mostly useful in analyzing sleep states. Hence, the IIR 6th order Butterworth filter is used to extract three frequency bands (alpha, beta, and gamma) on this work for emotion classification in PD and NC.

D. RQA feature extraction

Recurrence plot (RP) is used to analyze the complex system which is highly nonstationarity through visual analysis [11]. Recurrence Quantification Analysis (RQA) is used to study the behavior of the nonlinear system through performance measures in RP. RP is used to study the nonstationarity behavior as well as structural characteristics of a specific behavior [12]. Besides, RQA is highly successful in studying the physiological data with noise. Human brain signals are highly complex and nonstationary and RQA are highly useful to study the behavior of the system compared to other nonlinear methods. In this work, a set of two important performance measures of RP namely, Maximum Line Length (M_{line}) and Maximal Vertical Diagonal Length (V_{max}) among the eleven most common measures for emotion classification. From our earlier works, we found that the 6-*sec* segment gives significant information about emotional state changes in subjects [8]. Hence, the preprocessed and filtered data is segmented into 6-*sec* duration and two RQA features were extracted from each 6-*sec* segment for emotion classification.

Maximum Line Length (M_{line}) is used to measure the system divergence, which is reciprocal of approximate Largest Lyapunov Exponent (LLE). It measures the longest diagonal line on the RP by excluding the line of incidence. (Eqn 1)

$$M_{line} = \max(\{l_i;\ i=1,2,3,\ldots\ldots.N_i\}) \qquad \text{(Eqn 1)}$$

Maximum Vertical Line Length (V_{max}) is used to measure the longest vertical line in RP (Eqn 2)

$$V_{max} = \max(\{v_i;\ i=1,2,3,\ldots\ldots.N_v) \qquad \text{(Eqn 2)}$$

In this work, a sum of 11520 × 14 {(20 sub × 6 emotions × 6 trials × 8 segments × 2) × 14 channels} features were extracted in each frequency band of NC and PD subjects data. These features were used to classify the emotions using a nonlinear classifier.

E. Statistical analysis and cross-fold validation

The extracted features were used to study its significance in classifying emotions using an analysis of variance (ANOVA) method. Later, these features were used to split into training and testing sets of features using a *k* fold validation method with a *k* value of 5. The mean accuracy over 5 folds with standard deviation and the corresponding individual class accuracy is reported in the results and discussion section.

F. Emotion Classification

Extreme Learning Machine (ELM) classifier is used to classify the emotions of PD and NC using RQA features. ELM is a feed-forward neural network architecture with a single hidden layer. In this work, two different types of kernel functions used for classification such as multi-layer perceptron (MLP) and Radial Basis Function (RBF) [13]. Besides, four different activation functions (*hardlim*, *sigmoid*, *tanh*, and *gaussian*) at the output layer is also investigated to analyze the performance of ELM classifier in emotion classification. The network parameters of ELM namely, the number of hidden neurons for MLP and RBF kernel function and RBF width of RBF kernel function is studied through a grid search method by varying the parameter in specific ranges of values to analyze the performance of ELM in emotion classification.

The complete algorithm of feature extraction is performed using MATLAB software, and statistical analysis, box plot analysis, and ELM classification are performed by using Python toolboxes. The computing system is operating under the Windows Operating system and has an Intel *i7* processor with 16 GB RAM.

III. Experimental Results and Discussion

In this work, a sum of 40 subjects EEG data is used to develop an intelligent emotion classification system using an ELM classifier. Two RQA features were extracted from three different EEG frequency bands and classified using the ELM classifier. In addition, we also tested the combination of the Maximum Vertical Line Length and Maximum Line Length feature called ALL feature using the ELM classifier. This section discusses the performance of the ELM classifier in emotion classification using three types of features. After the feature extraction, the statistical features were analyzed using one way ANOVA for testing its significance in distinguishing six emotions of PD and NC. Table I presents the results of one way ANOVA of three features over three frequency bands. The results indicate that all the features have a value of $p<0.001$ and significant in differentiating emotions in both PD and NC. Besides, the F value of each feature in three frequency bands is also high in PD and NC. Among the three features, ALL features give the highest value of F in three frequency bands. Hence, these features can be used for emotion classification in PD and NC.

TABLE I. Statistical Analysis of Features through ANOVA

Frequency bands	Features	NC		PD	
		F	*p*	F	*p*
Alpha	M_{line}	30.99	1.25E-31	22.84	5.46E-23
	V_{max}	27.73	3.65E-28	17.52	2.15E-17
	ALL	**58.93**	**5.43E-16**	**35.85**	**3.59E-12**
Beta	M_{line}	21.59	1.13E-21	45.33	6.45E-47
	V_{max}	13.62	2.55E-13	39.29	1.83E-40
	ALL	**29.9**	**4.53E-19**	**62.92**	**9.29E-12**
Gamma	M_{line}	53.83	5.27E-56	76.74	1.51E-80
	V_{max}	53.3	1.94E-55	67.06	3.54E-70
	ALL	**90.23**	**3.49E-42**	**93.2**	**3.49E-19**

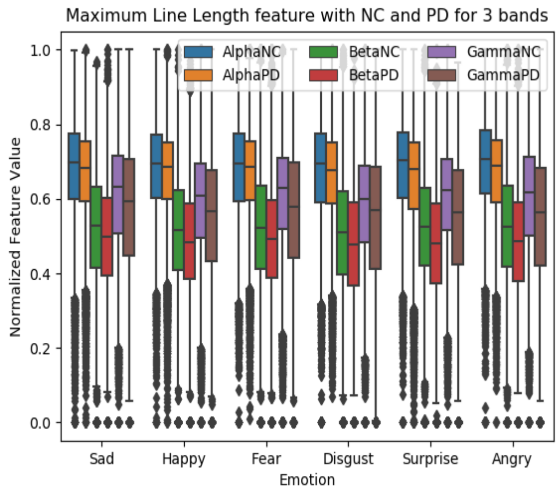

Fig. 2. Box plot analysis of the Maximum Line Length feature.

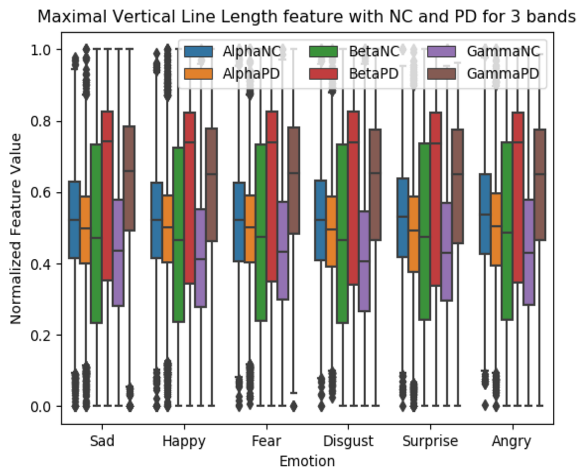

Fig. 3. Box plot analysis of the Maximum Vertical Line Length feature.

From the statistical features, we computed the mean, maximum, minimum, first quartile, second quartile, and the third quartile to analyze the characteristics of the normalized features between 0 and 1 through boxplot analysis. The box plot of maximum line length, maximal vertical line length, and ALL features were shown in Fig 2 – Fig 4. In Fig 2, the mean value of the feature in the beta band has lower normalized values in NC and PD over six emotions. However, the normalized feature means the value is higher in the alpha band and followed by gamma-band in NC and PD.

In the case of maximum vertical line length feature, the beta frequency band feature shows a higher mean value between emotions in NC and PD followed by gamma and alpha. However, the gamma band features of six emotions in NC and PD shows a significant difference in emotional experience in NC and PD compared to alpha and beta band. In Fig 4, the beta and gamma band have similar characteristics on six emotions in NC and PD than an alpha band. The alpha band features do not reflect any significant differences between emotions in NC and PD. However, the beta and gamma band feature has an ability to differentiate six different emotions in both NC and PD.

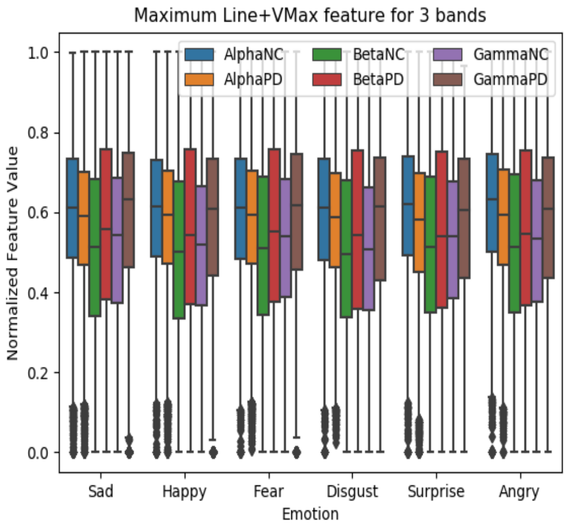

Fig. 4. Box plot analysis of Maximum Line Length and Maximum Vertical Line Length feature.

In ELM classification, the value of hidden neurons was varied in the range of 600 to 2000 with an increment of 20 for two different types of kernel functions (RBF and MLP). In the following section, we reported the highest mean accuracy corresponding to the number of hidden neurons in the fivefold cross-validation method and the individual classification accuracy. In RBF kernel-based ELM, the width of the RBF kernel is varied between 0.001 and 0.1 with an increment of 0.001 (from 0.001 to 0.01) and 0.01 (from 0.01 to 0.1). Table II shows the maximum mean emotion classification rate of NC and PD for maximum line length feature.

TABLE II. CLASSIFICATION OF EMOTIONS USING MAXIMUM LINE LENGTH FEATURE USING ELM

Frequency Band	Kernel	Parameters		Mean classification rate(in %) ± standard deviation	
		NC	PD	NC	PD
Alpha	**RBF**	**960, rbfw= 0.003**	**1080, rbfw= 0.003**	**79.10±0.45**	**77.98±0.76**
	tanh	940	980	78.70±0.57	77.55±0.67
	gaussian	920	1020	78.87±1.14	77.57±0.85
	sigmoid	1060	1000	78.87±1.06	77.58±0.71
	hardlim	1140	1400	76.72±2.26	75.88±1.13
Beta	**RBF**	**940, rbfw= 0.1**	**940, rbfw= 0.06**	**84.32±1.56**	**79.42±1.79**
	tanh	1100	940	84.02±1.44	78.78±1.79
	gaussian	1200	1000	83.78±1.04	79.03±1.04
	sigmoid	1160	940	83.90±1.65	79.33±0.76
	hardlim	1400	1400	80.50±1.64	76.75±1.41
Gamma	**RBF**	**1100, rbfw= 0.06**	**980, rbfw= 0.08**	**88.80±1.10**	**84.97±1.88**
	tanh	1220	1260	88.42±1.60	84.32±1.52
	gaussian	1260	1260	88.65±1.33	84.25±1.61
	sigmoid	940	1000	88.62±1.36	84.73±1.52
	hardlim	1400	1420	83.97±0.96	80.23±0.95

Among the three frequency band features, the gamma band gives the highest mean classification rate of 88.80% and 84.97% in NC and PD, respectively. In this multi-class problem, the RBF kernel performed well in differentiating the emotions compared to MLP kernel. Indeed, the accuracy of MLP kernel with the Gaussian activation function is closer to the accuracy of the RBF kernel. Compared to NC, the mean accuracy rate of PD subjects are lesser and it shows some emotional impairment in recognizing emotions in PD which might due to the loss of dopamine in the brain region.

The maximum vertical line length feature of RP gives the lower mean emotion classification rate compared to the maximum line length feature. Table III shows the mean classification rate of maximum vertical line length feature in the RQA analysis of NC and PD subjects. Further, the experimental results indicate that gamma-band features achieved the highest mean classification rate in NC and PD followed by beta and alpha band. A maximum means classification rate of 88.15% and 84.28% is achieved in NC and PD, respectively. The *hardlim* activation function gives the lowest classification rate compared to other activation functions in the present work.

TABLE III. CLASSIFICATION OF EMOTIONS USING MAXIMUM VERTICAL LINE LENGTH FEATURE USING ELM

Frequency Band	Kernel	Parameters		Mean classification rate(in %) ± standard deviation	
		NC	PD	NC	PD
Alpha	**RBF**	940, rbfw =0.03	900, rbfw= 0.003	79.00±1.14	78.00±1.14
	tanh	1100	680	79.17±1.86	77.83±1.96
	gaussian	960	660	79.00±0.84	78.17±1.03
	sigmoid	1080	920	79.00±1.63	77.50±0.77
	hardlim	1360	1380	76.67±1.36	76.00±0.41
Beta	**RBF**	920, rbfw= 0.04	1220, rbfw= 0.009	83.10±1.97	78.58±0.97
	tanh	1000	940	83.13±1.98	78.62±1.02
	gaussian	1080	hidden =960	83.02±1.00	78.68±1.38
	sigmoid	1180	1100	82.88±1.07	78.77±0.67
	hardlim	1320	1400	78.73±1.44	76.22±1.48
Gamma	RBF	1040, rbfw= 0.07	920, rbfw= 0.06	88.15±0.47	84.28±0.66
	tanh	1140	1280	88.28±1.85	83.53±0.66
	gaussian	1000	1020	88.20±0.93	83.13±1.19
	sigmoid	960	980	88.32±1.72	83.87±1.25
	hardlim	1340	1440	83.47±2.14	78.28±0.73

Finally, we tested the combination of maximum vertical line length and maximum line length features referred to ALL features for emotion classification in PD and NC. The experimental results of this combination of the feature are given in Table IV. Interestingly, the combination of features achieved a higher emotion classification rate than an individual feature. The maximum mean emotion classification rate of 89.17% is achieved on NC and 84.50% is achieved on PD. Furthermore, gamma-band gives more informative features for emotion classification compared to alpha and beta bands in both subjects. Also, the emotion recognition rate of PD is lesser than normal control in all types of features.

The emotion classification rate of individual classes corresponding to the feature which gives maximum mean emotion classification rate in three features (maximum line length, maximum vertical line length, and ALL (combination of two) features) is given in Fig 6 – Fig 8. In all types of features, gamma-band information is highly useful for identifying or recognizing different emotions in NC and PD subjects. Besides, the experimental results also indicate that the negative emotions (disgust, sadness, fear, and anger) in PD has the least accuracy than positive emotions (happiness and surprise). However, the normal control subjects have a fair accuracy in all classes of emotions and there is no deficiency can be found in NC.

TABLE IV. CLASSIFICATION OF EMOTIONS USING ALL FEATURE USING ELM

Frequency Band	Kernel	Parameters		Mean classification rate (in %) ± standard deviation	
		NC	PD	NC	PD
Alpha	**RBF**	**1060, rbfw= 0.001**	**1160, rbfw =0.003**	**79.47±0.84**	**77.83±1.89**
	tanh	920	1040	78.68±1.34	77.40±0.66
	gaussian	1040	1120	78.98±0.70	77.60±0.94
	sigmoid	920	940	78.98±1.06	77.55±1.04
	hardlim	1300	1080	76.92±1.25	75.87±0.90
Beta	**RBF**	**1040, rbfw= 0.09**	**980, rbfw= 0.08**	**84.32±1.71**	**79.30±0.96**
	tanh	960	980	83.58±1.87	78.83±0.75
	gaussian	1220	1020	83.48±0.99	78.83±1.18
	sigmoid	1060	940	84.08±1.51	79.07±1.43
	hardlim	1380	1060	80.37±1.67	77.08±1.58
Gamma	**RBF**	**900, rbfw= 0.1**	**1040, rbfw= 0.07**	**89.17±0.87**	**84.50±0.48**
	tanh	1080	1140	88.12±1.19	84.00±1.65
	gaussian	1280	1220	88.10±1.52	83.98±1.43
	sigmoid	1120	1040	88.50±1.59	83.72±1.32
	hardlim	1440	1480	83.90±1.03	80.17±1.60

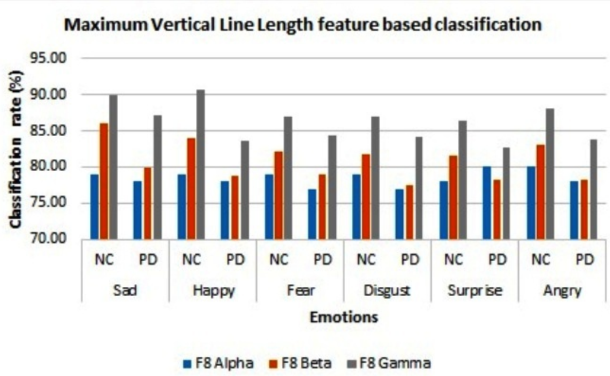

Fig. 5. Individual class accuracy of Maximum Line Length feature using ELM

In this work, the ELM classifier gives a higher emotion recognition rate compared to the other classifiers used in our earlier work. The comparison of results of present work with our earlier work is given in Table V. Besides the higher accuracy, ELM performs faster classification than other machine learning methods. Indeed, the performance of the ELM highly depends on its hyper-parameters (hidden neurons, RBF width). Though the computational system takes time for tuning the parameters to achieve a higher classification rate, it's still less compared to other complex machine learning algorithms.

Though the proposed system efficiently classifies the emotions of NC and PD with higher recognition rate, it still has challenges in improving the system performance for robust system development and the possible future work: (a) different types of features from RQA such as recurrence rate, entropy, and other features can be computed and used for emotion classification (b) different types of machine learning algorithms such as k Nearest Neighbor, Probabilistic Neural Network (PNN), Neuro-Fuzzy classifiers, etc can be used to compare the performance of emotion classification in NC and PD. (c) the recent development of deep learning methods can be utilized to classify the emotions.

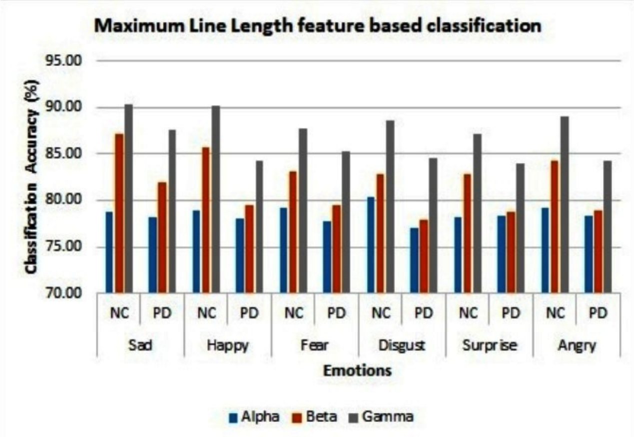

Fig. 6. Individual class accuracy of Maximum Vertical Line Length feature using ELM

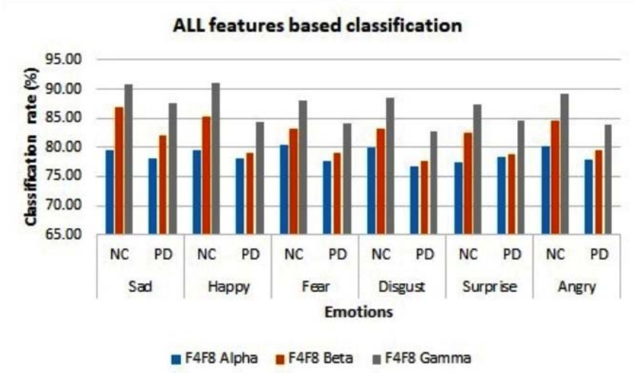

Fig. 7. Individual class accuracy of ALL feature using ELM

IV. CONCLUSION

Recurrence Quantification Analysis (RQA) features are used for emotion classification in NC and PD. Two most significant RQA features namely Maximum Vertical Line Length and Maximum Line Length features were extracted from alpha, beta, and gamma band of NC and PD subjects EEG data. Besides, the combination of two features also tested in the present work in classifying emotions of NC and PD. ELM classifier is used to classify the emotions and achieved a maximum mean emotion classification rate of 89.17% and 84.50% in NC, and PD, respectively. With the limited number of subjects in PD and NC, the proposed method results in higher emotion recognition rate compared to other works in the literature. The experimental results reveal that, the negative emotions (sadness, anger, fear and disgust) shows lesser recognition rate compared to positive emotions (happiness and surprise) in PD and gamma band play a significant role in detecting emotions in NC and PD compared to other EEG frequency bands. Our future work focuses on improving the emotion recognition rate of NC and PD using other types of RQA features and to classify the emotions using different machine learning algorithms and deep learning methods.

TABLE V. COMPARISON OF EMOTION CLASSIFICATION IN PD USING EEG SIGNALS WITH EARLIER WORKS

Ref	Mean		Happiness		Sadness		Anger		Fear		Disgust		Surprise	
	NC	PD	NC	PD	NC	PD	NC	PD	NC	PD	NC	PD	NC	PD
8	87.34	83.70	90.27	85.85	90.29	78.87	77.29	90.84	89.20	80.32	88.05	78.96	88.98	87.36
9	71.79	51.66	Not given											
10	81.72	82.70	89.26	91.25	76.65	83.35	81.70	80.37	79.25	80.50	70.25	73.50	93.25	87.28
Present work	**89.17**	**84.50**	**90.90**	**87.50**	**91.10**	**84.30**	**88**	**84.10**	**88.5**	**82.70**	**87.4**	**84.60**	**89.10**	**83.80**

ACKNOWLEDGMENT

This work is financially supported by the Kuwait Foundation of Advancement of Sciences through an exploratory research grant. (Grant No: PR18-13MM-08).

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